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36-402/608 ADA-II  
Breakout #24 Comments

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Job Search Intervention Study (JOBS II) is a randomized field experiment that investigates the efficacy of a job training intervention on unemployed workers. The program is designed to not only increase reemployment among the unemployed but also enhance the mental health of the job seekers. In the JOBS II field experiment, 1,801 unemployed workers received a pre-screening questionnaire and were then randomly assigned to treatment and control groups. Those in the treatment group participated in job-skills workshops. In the workshops, respondents learned job-search skills and coping strategies for dealing with setbacks in the job-search process. Those in the control condition received a booklet describing job-search tips. In follow-up interviews, the two key outcome variables were measured; a continuous measure of depressive symptoms based on the Hopkins Symptom Checklist which gives a value between 0 and 5 with 2 decimal places, and a binary variable, representing whether the respondent had become employed.

```
library("mediation")  
data("jobs")  
summary(jobs)
```

treat	econ_hard	depress1	sex	age
Min. :0.0000	Min. :1.000	Min. :1.00	Min. :0.0000	Min. :17.49
1st Qu.:0.0000	1st Qu.:2.330	1st Qu.:1.36	1st Qu.:0.0000	1st Qu.:29.30
Median :1.0000	Median :3.000	Median :1.83	Median :1.0000	Median :36.64
Mean :0.6674	Mean :3.024	Mean :1.87	Mean :0.5362	Mean :37.57
3rd Qu.:1.0000	3rd Qu.:3.670	3rd Qu.:2.36	3rd Qu.:1.0000	3rd Qu.:44.62
Max. :1.0000	Max. :5.000	Max. :3.00	Max. :1.0000	Max. :72.48

	occp	marital	nonwhite	educ
professionals	:175	nev marr:279	white0 :747	lt-hs : 50
manegerial	:168	married:408	non.white1:152	highsc:272
clerical/kindred	:217	separtd: 30		somcol:319
sales workers	: 65	divrcd :163		bach :146
craftsmen/foremen/kindred	: 97	widowed: 19		gradwk:112
operatives/kindred wrks	: 93			
laborers/service wrks	: 84			

income	job_seek	depress2	work1	job_dich
1t15k :164	Min. :1.000	Min. :1.000	psyump:606	Min. :0.0000
15t24k:206	1st Qu.:3.667	1st Qu.:1.273	psyemp:293	1st Qu.:0.0000
25t39k:218	Median :4.167	Median :1.600		Median :1.0000
40t49k:110	Mean :4.043	Mean :1.741		Mean :0.6174
50k+ :201	3rd Qu.:4.667	3rd Qu.:2.091		3rd Qu.:1.0000
	Max. :5.000	Max. :4.909		Max. :1.0000

control	job_disc
Min. :0.0000	Low-Med : 24
1st Qu.:0.0000	Medium :138
Median :0.0000	Med-High:438
Mean :0.3326	High :299
3rd Qu.:1.0000	
Max. :1.0000	

Consider the model to test whether the effects of the workshops (treat) on depression at the time of follow-up (depress2) is mediated through increasing job seeking actions (job\_seek, considered to be on a quantitative scale), correcting for pretreatment level of depression (depress1), education, income, race, marital status, age, sex (a female indicator), previous occupation (occp), and the level of economic hardship (econ\_hard).

**Question 1: Draw the DAG.**

The DAG is

$$T \rightarrow M \rightarrow Y$$

but with many arrows from age, sex, race, etc. going into both M and Y.

```

model.m <- lm(job_seek ~ treat + depress1 + econ_hard + sex +
              age + occp + marital + nonwhite + educ + income,
              data = jobs)

summary(model.m)
# Coefficients:              Estimate Std. Error t value Pr(>|t|)
# (Intercept)              3.8806256  0.1947174  19.930 < 2e-16 ***
# treat                    0.0774238  0.0492939   1.571 0.116624
# depress1                 -0.2540256  0.0440638  -5.765 1.13e-08 ***
# econ_hard                0.1036040  0.0265612   3.901 0.000103 ***
# sex                     -0.0053180  0.0542355  -0.098 0.921913
# age                      0.0005308  0.0026550   0.200 0.841575
# occpmanegerial          0.0056477  0.0766773   0.074 0.941302
# occpclerical/kindred    -0.1132352  0.0777967  -1.456 0.145883
# occpsales workers       -0.0137738  0.1012484  -0.136 0.891821
# occpcraftsmen/foremen/kindred -0.2015647  0.0965720  -2.087 0.037160 *
# occpoperatives/kindred wrks -0.2959024  0.0999259  -2.961 0.003147 **
# occplaborers/service wrks -0.3565544  0.1019639  -3.497 0.000494 ***
# maritalmarried          0.0381422  0.0667623   0.571 0.567934
# maritalsepartd          0.3641314  0.1365291   2.667 0.007793 **
# maritaldivrcd           0.2041101  0.0770659   2.649 0.008230 **
# maritalwidowed         -0.3301324  0.1761481  -1.874 0.061240 .
# nonwhitenon.white1     0.0615794  0.0651346   0.945 0.344707
# educhighsc              0.1813264  0.1088818   1.665 0.096201 .
# educsomcol              0.1638371  0.1097146   1.493 0.135719
# educbach                0.2563072  0.1220038   2.101 0.035943 *
# educgradwk             0.2013935  0.1293041   1.558 0.119709
# income15t24k            0.1583888  0.0753071   2.103 0.035730 *
# income25t39k            0.0898314  0.0776033   1.158 0.247355
# income40t49k            0.1999402  0.0941763   2.123 0.034031 *
# income50k+              0.1631108  0.0888391   1.836 0.066694 .

```

**Question 2: What does this model tell us? Which causal step is tested here?**

This tests the effects of treatment (workshops) on the mediator (job seeking actions) correcting for the covariates. Mediation seems unlikely (impossible with the causal steps approach) because there is not a statistically significant effect of T on M. Interestingly pretreatment depression and manual labor jobs (compared to professional jobs) decrease job seeking, while economic hardship separated or divorced marital status (compared to single), a bachelor's degree (compared to less than high school) and higher incomes (compared to the lowest income) increase job seeking.

```

model.y <- lm(depress2 ~ treat + job_seek + depress1 + econ_hard +
              sex + age + occp + marital + nonwhite +
              educ + income, data = jobs)

summary(model.y)
# Coefficients:              Estimate Std. Error t value Pr(>|t|)
# (Intercept)              1.4527281  0.1940639   7.486 1.74e-13 ***
# treat                    -0.0367886  0.0407940  -0.902  0.36740
# job_seek                 -0.1773802  0.0279535  -6.346 3.56e-10 ***
# depress1                  0.4098612  0.0371003  11.047 < 2e-16 ***
# econ_hard                 0.0679692  0.0221404   3.070  0.00221 **
# sex                       0.0621566  0.0448206   1.387  0.16586
# age                       0.0007858  0.0021942   0.358  0.72034
# occpmanegerial           0.0664879  0.0633665   1.049  0.29435
# occpclerical/kindred     0.0503458  0.0643692   0.782  0.43434
# occpsales workers       -0.0348333  0.0836727  -0.416  0.67729
# occpcraftsmen/foremen/kindred -0.0290567  0.0800059  -0.363  0.71656
# occpoperatives/kindred wrks  0.1635053  0.0829922   1.970  0.04914 *
# occplaborers/service wrks -0.0215721  0.0848505  -0.254  0.79937
# maritalmarried          -0.0072627  0.0551828  -0.132  0.89532
# maritalsepartd          0.2019970  0.1132861   1.783  0.07492 .
# maritaldivrcd           -0.0453020  0.0639424  -0.708  0.47884
# maritalwidowed          0.0923133  0.1458613   0.633  0.52697
# nonwhitenon.white1     -0.1081444  0.0538549  -2.008  0.04494 *
# educhighsc              -0.0023664  0.0901228  -0.026  0.97906
# educsomcol               0.0226457  0.0907839   0.249  0.80307
# educbach                 0.0148269  0.1010784   0.147  0.88341
# educgradwk              0.1782504  0.1070053   1.666  0.09611 .
# income15t24k            -0.0486597  0.0623912  -0.780  0.43565
# income25t39k            -0.0208905  0.0641806  -0.325  0.74488
# income40t49k            -0.0528838  0.0780279  -0.678  0.49811
# income50k+              -0.1179727  0.0735582  -1.604  0.10912

```

**Question 3: What does this model tell us? Which causal step is tested here?**

We can see that job-seeking is (negatively) associated with depression at follow-up. This confirms one step of the causal steps strategy ( $b \neq 0$ ). The treatment coefficient does get closer to zero, so this supports the step of the causal steps strategy for partial mediation that says that the treatment coefficient drops when the mediator is present, but its all probably noise. We also note that depression is less severe in non-whites (than whites) and more severe for this with greater initial depression, for those with economic hardship, and for “operative” workers compared to professionals.

The Sobel test defines  $a$  as the coefficient of T in the regression of M on T and X, and  $b$  as the coefficient of M in the regression of Y on M, T, and X. In the mediation literature the notation for the *sampling* variance of these coefficients (square of the standard errors of the coefficients) is  $s_a^2$  and  $s_b^2$ . The Sobel test is a Z-test of  $H_0 : ab = 0$  using  $SE_{ab} = \sqrt{a^2 s_b^2 + b^2 s_a^2 + s_a^2 s_b^2}$ .

**Question 4: Find the values needed for this formula in the above results. If you have access to the web, calculate the Sobel test with <http://people.ku.edu/~preacher/sobel/sobel.htm> (or use a calculator). Note that the sampling distribution of a product is often not normal, so this test may be unreliable.**

a=0.0774, SE(a)=0.0493

b=-0.1774, SE(b)=0.0280.

The SE of  $(ab)$  is 0.00901, the Sobel statistic  $(ab/SE(ab))$  is -1.52 which gives a p-value of 0.128, so we retain the null hypothesis of no mediation of the effects of workshops on depression via job-seeking.

Use the notation T for the treatment of interest, M for the mediator, X for pre-treatment covariates, and Y for the outcome. The actual mediation analysis is performed by the `mediate()` function using a model of M on T and X (called `model.m`), and a model of Y on M, T and X (called `model.y`). Models other than `lm()`, such as `glm()`, are allowed. Two methods are provided, but they tend to give similar results.

Important technical detail: “These two model objects, `model.m` and `model.y`, become the arguments for the `mediate()` function. The analyst must take some care with missing values before estimating the models above. While model functions in R handle missing values in the data using the usual listwise deletion procedures, the functions in mediation assume that missing values have been removed from the data before the estimation of these two models. Thus the data for the two models must have identical observations sorted in the same order with all missing values removed.”

```
out.1 <- mediate(model.m, model.y, sims = 1000, boot = TRUE,
                treat = "treat", mediator = "job_seek")
summary(out.1)
# Causal Mediation Analysis
# Confidence Intervals Based on Nonparametric Bootstrap
# Mediation Effect:  -0.01371 95% CI  -0.033558  0.002373
# Direct Effect:    -0.03779 95% CI  -0.1164  0.0374
# Total Effect:    -0.0515 95% CI  -0.13155  0.02468
# Proportion of Total Effect via Mediation:  0.2217 95% CI  -1.944  2.643
```

The “Mediation Effect” is the product  $ab$ , i.e., the (estimated) mediated effect of a one unit change in T on Y. The output labeled “Direct Effect” is the direct effect of T on Y, which would be zero in the case of complete mediation.

```
out.2 <- mediate(model.m, model.y, sims = 1000, treat = "treat",
                mediator = "job_seek")
summary(out.2)
# Causal Mediation Analysis
# Quasi-Bayesian Confidence Intervals
# Mediation Effect:  -0.01366 95% CI  -0.031616  0.002241
# Direct Effect:    -0.03821 95% CI  -0.11495  0.04142
# Total Effect:    -0.05187 95% CI  -0.13195  0.03282
# Proportion of Total Effect via Mediation:  0.2133 95% CI  -2.651  2.061
```

**Question 5: Do we have evidence that job seeking actions mediate the effect of the workshops on depression at the time of follow-up?**

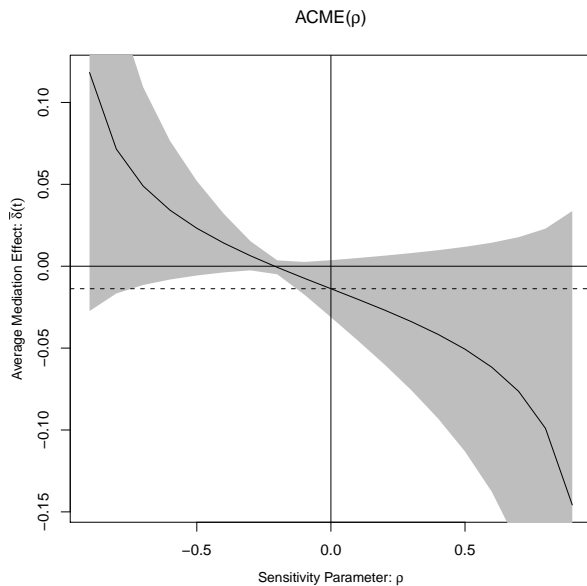
Using either analysis, the CI for mediation includes zero, so we retain  $H_0$  of no mediation. Note how unreliable the CI for the proportion of the effect due to mediation can be: although the value must be between 0 and 1, the CI includes values far outside that.

A key assumption of causal mediation, even in the presence of randomized treatment assignment is that there is no unmeasured “Z” that affects (“causes”) both M and Y. It is often hoped that measuring sufficient pre-treatment covariates (X’s) will preclude the presence of any important unmeasured Z’s. The assumption can be expressed in the form  $\rho = 0$  where  $\rho$  is the correlation of  $\epsilon_1$  and  $\epsilon_2$  in the equations

$$\begin{aligned} M_i &= T_i\beta + X_i\gamma + \epsilon_{i1} \\ Y_i &= T_i\beta + X_i\gamma + M_i\theta + \epsilon_{i2} \end{aligned}$$

The assumption is untestable, but we can perform “sensitivity analysis”.

```
plot(medsens(out.1))
```



**Question 6: ACME means Average Causal Mediation Effect. Interpret the plot. Give plausible examples of a unmeasured confounders that induce positive and negative error correlations.**

The plot shows that no matter what the true (unknowable) correlation of the errors is, we would still retain  $H_0$ . Unmeasured individual tendencies toward pessimism would make one less likely to job seek and more depressed, causing negative error correlation. An individual situation of special economic hardship beyond what the econ.hard variable measures would cause more depression and more job seeking, which is positive correlation.

```

model.yw <- glm(work1 ~ job_seek + treat + depress1 + econ_hard +
               sex + age + occp + marital + nonwhite + educ + income,
               data = jobs, family=binomial)
summary(model.yw)
# Coefficients:                Estimate Std. Error z value Pr(>|z|)
# job_seek                    0.228010   0.109752   2.077   0.0378 *
# treat                       0.279319   0.160911   1.736   0.0826
# ...
out.w <- mediate(model.m, model.yw, sims = 1000, treat = "treat",
                 mediator = "job_seek")
summary(out.w)
# Mediation Effect:  0.003666 95% CI -0.0009565  0.0108308
# Direct Effect:    0.05476 95% CI -0.006568  0.119461
# Total Effect:     0.05843 95% CI -0.003512  0.124070
# Proportion of Total Effect via Mediation:  0.0576 95% CI -0.2573  0.3555

```

**Question 7: How does this analysis differ from above? Important note: mediate() is valid in this case, but the Sobel test based on the usual SE formula is not.**

The outcome is binary, so we *must* use logistic (or probit) regression. Again we have no evidence that job seeking mediates the effects of the workshops on actually getting a job as shown by the CI coverage of 0 for the mediation effect.